

Definitions of stable distributions/processes

A central limit theorem for i.i.d. random variables

Mixing and Quantitative ergodicity for Markov chains

Convergence to stable processes

Functional limit Theorem for some functional for Markov chains

Some examples

Limits theorems for some functionals of Markov chains with heavy tails: convergence to stable process with index $\alpha \in (0, 2)$

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Stable distributions/Processes with index α , Definitions

Stable distributions

A random variable (r.v.) X has a stable law if there exists constants $c_n > 0$ and $d_n \in \mathbb{R}$ such that:

$X_1 + \dots + X_n \stackrel{d}{=} c_n X + d_n \quad \forall n \geq 1$, where $X_i, i \geq 1$ are i.i.d copy of X .

- If $d_n = 0$ one says that X is strictly stable.
- For such a distribution, it is known that $c_n = cst n^{1/\alpha}$ with $\alpha \in]0, 2]$.
- α is called the index of stability.
- if $\alpha = 2$, X is the gaussian r.v.
- We'll say that X is an α -stable r.v or simply α -stable.

The Lévy Khintchine representation

- In the case $\alpha \in (0, 2)$ one specifies the characteristic function of an α -stable random variable X as follows $\mathbb{E}e^{i\theta X} = e^{\psi(\theta)}$ where

$$\psi(\theta) = ib\theta + \int (e^{i\theta x} - 1 - i\theta x 1_{|x| \leq 1}) \frac{1}{|x|^{1+\alpha}} (c_1 1_{x < 0} + c_2 1_{x > 0}) dx,$$

with $c_1, c_2 \geq 0$ and $c_1 + c_2 > 0$. We'll say that X is α -stable with characteristics (b, c_1, c_2) .

- Other representations exist, [Samorodnisky and Taqqu], [Zolotarev] but they are the same.
- In the sequel, an α -stable process $(X_t, t \geq 0)$ is a Lévy process such that the r.v. X_1 is α -stable.

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The generalized Central Limit Theorem (GCLT)

GCLT, [Gnedenko-Kolmogorov]

Let $(X_i)_{i \geq 1}$ be iid random variables with common cumulative distribution function F . Denotes by Y_α an α -stable with local characteristics (c_1, c_2) . There exists suitable constants $a_n > 0$, $b_n \in \mathbb{R}$ such that

$$a_n^{-1} \sum_{i=1}^n X_i - b_n \xrightarrow{d} Y_\alpha$$

if and only if $G(x) = 1 - F(x) - F(-x)$ is regularly varying of order $-\alpha$ and

$$\lim_{x \rightarrow \infty} \frac{1 - F(x)}{1 - F(x) + F(-x)} = \frac{c_1}{c_1 + c_2}, \quad \lim_{x \rightarrow \infty} \frac{F(-x)}{1 - F(x) + F(-x)} = \frac{c_2}{c_1 + c_2}$$

Example

- The Pareto distribution X of type I, with tail distribution $\mathbb{P}[X > x] = c x^{-\alpha} \mathbb{I}_{x>0}$ with $c > 0$ and $\alpha \in (0, 2)$, belongs
- Let $Z \sim \Gamma(a, \lambda)$, where $\Gamma(a, \lambda)$ is the Gamma distribution with parameters a and $0 < \lambda < 2$. Define $X = e^Z$. We have $\mathbb{P}[X > x] \sim y^{-\lambda} L(y)$ for some slowly varying function L so that $X \in \mathcal{D}(\alpha, Y_\alpha)$.
- (a_n) can be taken to be $a_n = n^{1/\alpha}$
- and if $\alpha \in (1, 2)$ we can take $b_n = n\mathbb{E}(X)$ and $b_n = 0$ for $\alpha \in (0, 1)$.
- If $\alpha = 2$, this result improves in particular the CLT.

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Mixing sequences

- Let \mathcal{F}_j (resp. \mathcal{G}_j) be respectively the past and the future σ -fields generated by a sequence (X_n) for $0 \leq n \leq j$ (resp. $j \leq n$).

Strongly Mixing [Bradley, Rio]

The strong mixing coefficient $\alpha(n)$ is defined as :

$$\alpha(n) = \sup_j \{ \sup_{A, B} (\mathbb{P}(A \cap B) - \mathbb{P}(A)\mathbb{P}(B)) \mid A \in \mathcal{F}_j, B \in \mathcal{G}_{j+n} \}.$$

- If $\lim_{n \rightarrow \infty} \alpha(n) = 0$, the sequence is strongly mixing.

ρ -Mixing and φ -Mixing [Peligrad, Doukhan]

The ρ -mixing coefficient $\rho(n)$ is defined as the maximal correlation coefficient, i.e.

$$\rho(n) = \sup_j \{ \sup_{F,G} \text{Corr}(F, G), F \in L^2(\mathcal{F}_j), G \in L^2(\mathcal{G}_{n+j}) \}.$$

The φ -mixing coefficient $\varphi(n)$ is defined as:

$$\varphi(n) = \sup_j \{ \sup_{A,B} (\mathbb{P}(B|A) - \mathbb{P}(B)) , A \in \mathcal{F}_j, B \in \mathcal{G}_{j+n} \}.$$

- If $\lim_{n \rightarrow \infty} \rho(n) = 0$ the sequence is ρ -mixing.
- If $\lim_{n \rightarrow \infty} \varphi(n) = 0$, the sequence is φ -mixing.

Quantitative ergodicity for Markov chains

- Let (X_n) be an irreducible, aperiodic and positive recurrent Markov chain with invariant probability measure μ . We denote by P the transition kernel of the chain.

Rates of ergodicity

For $p, r \geq 1$ we define

$$\alpha_{r,p}(n) = \sup \left\{ \|P^n g\|_{L^p(\mu)}, \forall g : \|g\|_{L^r(\mu)} = 1 \text{ and } \int g d\mu = 0 \right\}$$

We define similarly $\alpha_{p,r}^*(n)$ for the adjoint operator P^* .

- Interesting rates in the sequel are the following: $\alpha_{2,2}$ or $\alpha_{p,p}$, $\alpha_{\infty,2}$ and $\alpha_{1,\infty}$

- $\alpha_{2,2}$ or $\alpha_{2,2}^*$ is given by the following well known spectral gap estimate:

Proposition

Under the previous assumptions for the chain, the following are equivalent

- (1) $\forall f \in \mathbb{L}^2(\mu)$ and all n , $\text{Var}_\mu(P^n f) \leq e^{-2\lambda n} \text{Var}_\mu(f)$,
- (2) there exists $C \geq 1$, such that $\forall f \in \mathbb{L}^2(\mu)$,

$$\text{Var}_\mu(f) \leq C \langle (I - P^*P)f, f \rangle := \int (f - P^*Pf) f d\mu,$$

where C is given by the relation $e^{-\lambda} = \frac{C-1}{C}$.

- This shows that $\alpha_{2,2}(n) \leq e^{-\lambda n}$ for f such that $\mu(f) = 0$ and $\|f\|_2 = 1$. It follows also that $\alpha_{p,p}(n) \leq 2e^{-\lambda n 2 \frac{(p-1)}{p}}$ for all $p > 1$.

Example

- Consider the Birth and death chain (BDC) in the space \mathbb{N}

$$P(x, x+1) = p_x > 0, \quad P(x, x-1) = q_x > 0,$$

$$P(x, x) = 1 - p_x - q_x, \quad q_0 = 0$$

The chain is positively recurrent if and only if

$$\sum_{x>0} \frac{p_0 p_1 \dots p_{x-1}}{q_1 \dots q_x} := \sum_{x>0} \lambda_x < +\infty,$$

in which case, the unique invariant (reversible) distribution is given by $\mu(x) = \mu(0) \lambda_x$ for all $x > 0$.

- It is well known that there exist a spectral gap provided

$$q_x \geq \frac{(d+1)b}{b-1} + bp_x \quad \text{for some } b > 1 \text{ and } d > 0$$

Example

- The reflected random walk on \mathbb{N} is given from (BDC) when p_x and q_x are constant:

$$p_x = p, \quad q_x = q = 1 - p, \quad \text{and} \quad P(x, x) = 0 \text{ if } x \neq 0$$

The chain is positive recurrent if $q > p$ and the invariant distribution (reversible) is the geometric distribution on \mathbb{N}

$$\mu(dx) = (1 - \frac{p}{q})(\frac{p}{q})^x$$

- The above spectral gap condition for (BDC) enforces the parameters to be $q > p$ for the reflected random walk.

About $\alpha_{\infty,2}$.

- It can be compute in terms of weak Poincaré inequalities. We call weak Poincaré inequality (WPI), an inequality of the form:

$$\text{Var}_{\mu}(f) \leq \beta(s) \langle (I - P^*P)f, f \rangle + s \|f - \mu(f)\|_{\infty}^2 \quad s \in (0, 1] \quad (\spadesuit),$$

where β is a non increasing function.

- In the continuous time case, but using derivatives, this was introduced by **M. Röckner and F.Y. Wang**.

Proposition

- If the (WPI) in (\spadesuit) holds for some non increasing function β , then $\alpha_{\infty,2}(n)$ and $\alpha_{\infty,2}^*(n)$, $\rightarrow 0$ as $n \rightarrow \infty$.
- Conversely, if P is symmetric, any decay to 0 of $\alpha_{\infty,2}(n)$ will imply some (WPI) in (\spadesuit).

In general however, we do not know whether $\alpha_{\infty,2}$, $\alpha_{\infty,2}^*$ are equal or have the same behaviour.

About $\alpha_{1,\infty}$ or $\alpha_{1,\infty}^*$.

- The rate $\alpha_{1,\infty}(n)$ specifies that the semi group $(P_n, n \geq 0)$ is hyperbounded (hypercontractivity or ultracontractivity) and can be described in terms of log-Sobolev inequalities.

Link between Mixing property and ergodicity property.

Proposition

For all n , let $[n]$ denotes the integer part of n .

$$(1) \quad \alpha_{\infty,2}^2(n) \vee (\alpha^*)_{\infty,2}^2(n) \leq 4\alpha(n) \leq \alpha_{\infty,2}([n/2]) \alpha_{\infty,2}^*([n/2]).$$

(2)

$$\alpha_{2,2}^2(n) = (\alpha^*)_{2,2}^2(n) \leq \rho(n) \leq c \alpha_{2,2}(n).$$

$$(3) \quad \varphi(n) \leq \alpha_{1,\infty}^2([n/2]).$$

Idea of the proof

- Use equivalent definitions of Mixing coefficients in terms of covariance representations, and the Markov property.

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Definition

- We shall say that a random variable Z_1 is regularly varying of index $\alpha > 0$ if there exist some $c \in [0, 1]$ such that for all $x > 0$,

$$\lim_{u \rightarrow +\infty} \frac{\mathbb{P}(Z_1 > ux)}{\mathbb{P}(|Z_1| > u)} = cx^{-\alpha}, \quad \lim_{u \rightarrow +\infty} \frac{\mathbb{P}(Z_1 < -ux)}{\mathbb{P}(|Z_1| > u)} = (1-c)x^{-\alpha}$$

- If Z_1 is regularly varying, there exists a slowly varying function L such that for all $x > 0$,

$$\mathbb{P}(|Z_1| > x) = x^{-\alpha} L(x).$$

- Note that for $\alpha \in (0, 2)$, this allows to deal with non square integrable random variables.

Limits theorems for stationary regularly and mixing sequences

Let $(Z_i)_{i \geq 1}$ be a stationary and regularly varying sequences and denotes by S_n , the partial sum sequences

- When dealing with convergence to stable distributions/processes, we need some kind of centering , namely we shall consider:

$$T_n = \frac{S_n - nc_n}{a_n}, \quad T_n(t) = \frac{S_{[nt]} - ntc_n}{a_n}$$

where $c_n = \mathbb{E}[Z_1 1_{|X_1| \leq a_n}]$ and a_n is defined by $\lim_{n \rightarrow \infty} n\mathbb{P}[|Z|_1 > a_n] = 1$.

- It is interesting to look at the asymptotic behavior of

$$\frac{nc_n}{a_n} = \frac{n}{a_n} \mathbb{E} [Z_1 \mathbb{I}_{|Z_1| \leq a_n}]$$

Proposition

For $\alpha \in (1, 2)$ and $\mathbb{E}_\mu(Z_1) = 0$ we have

$$\lim_{n \rightarrow +\infty} \frac{n c_n}{a_n} = \frac{\alpha}{1 - \alpha} (2c - 1).$$

- The same relation holds in the case $\alpha \in (0, 1)$ (thanks to Karamata Theorem).
- This proposition allows to deal only with $S_{[nt]}$ up to some slight change in the characteristics of the limit process.

About the literature in the context of Mixing sequences

- (1)[Davis] **R.Davis** Stable limits for partial sums of dependent random variables, Ann.Probab. n11, 262-269, (1983).
- (2) [TK] **M.Tyran-Kaminska**. Convergence to Lévy stable processes under some weak dependence conditions. Stochastic Process. Appl. 120, n9, 1629-1650, (2010)
- (3) [BKS] **B.Basrak, D.Krizmanic, and J.Seger**. A functional limit theorem for dependent sequences with infinite variance stable limits. Ann.Probab. 40, N5 2008-2033 (2012).
- (4) [BJMW] **K.Bartkiewicz and Al**. Stable limits for sums of dependent infinite variance random variables. Probab.Theory Relat.Fields, 150: 337-372, (2011).

- The following condition called the **Anti-clustering conditions** (AC) which is familiar from extreme value theory, is relevant when dealing with convergence to α -stable process.

Sufficient Anti Clustering Condition (AC)

$$\lim_{k \rightarrow +\infty} \limsup_{n \rightarrow +\infty} \sum_{j=2}^{[n/k]} n \mathbb{P}_{\mu}(|Z_1| > \varepsilon a_n, |Z_j| > \varepsilon a_n) = 0, \quad \forall \varepsilon > 0.$$

- Such conditions are assumed in the above papers, namely known as : condition \mathcal{D}' of **R.Davis**, condition (x) of **Denker and Jakubowski**.

Necessary Anti Clustering Condition (NAC)

A necessary Anti clustering condition is described by the following condition: (Condition (3.19) in [M.Tyran-Kaminska])

$$\lim_{n \rightarrow +\infty} \mathbb{P}_\mu \left(\max_{2 \leq j \leq r(n)} |Z_j| > \varepsilon a_n \mid |Z_1| > \varepsilon a_n \right) = 0. \quad r(n) = o(n)$$

- In the previous we discussed spectral gap properties and compared them to mixing properties.
- Now, once this correspondance is understood, the only thing to do, is to check the so called "Anti clustering" conditions.

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Theorem

Let $(X_n)_{n \geq 0}$ be an irreducible, aperiodic and positive recurrent Markov chain with unique invariant probability measure μ . Let f be such that $Z_1 = f(X_1)$ is regularly varying of index $\alpha \in (1, 2)$ and $\int f d\mu = 0$.

① Assume that the chain has a spectral gap.

② If $P|f|$ or $P^*|f|$ belongs to $\mathbb{L}^{\alpha+\beta}(\mu)$ for some $\beta > 0$ then

$\frac{1}{a_n} S_{[nt]}(f) = \frac{1}{a_n} \sum_{j=1}^{[nt]} f(X_j)$ converges (under \mathbb{P}_μ), in the Skorohod topology to an α -stable process.

- A CLT of this kind was obtained in 2009 by [**M.Jara, T.Komorowski and S.Olla**] "Limits Theorems for additive functionals of a Markov chain". Ann. of Applied Probab., 19(6): 2270-2300, (2009) using martingale approximation.

The next result contains the case $\alpha \in (0, 1]$.

Theorem

Let $(X_n)_{n \geq 0}$ be an irreducible, aperiodic and positive recurrent Markov chain with unique invariant probability measure μ . Let f be such that $Z_1 = f(X_1)$ is regularly varying of index $\alpha \in (0, 2)$. Assume that f is symmetric under \mathbb{P}_μ in the case $\alpha = 1$.

- ① Assume also that the chain has a spectral gap.
- ② If for some $\eta \leq \alpha$, $f \in \mathbb{L}^\eta(\mu)$ and $P|f|^\eta$ or $P^*|f|^\eta$ belongs to $\mathbb{L}^{1+\beta}(\mu)$ for some $\beta > 0$ such that $\eta > \frac{\alpha}{(1+\beta)}$, then

$\frac{1}{a_n} S_{[nt]}(f) = \frac{1}{a_n} \sum_{j=1}^{[nt]} f(X_j)$ converges (under \mathbb{P}_μ), in the Skorohod topology to an α -stable process.

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Example

- For the reflected random walk, the Necessary Anti clustering Condition (NAC) fail to holds.
- A nice example of Markov chain in superdiffusion of energy in a lattice dynamic was studied by **[Jara,Olla,Komorowski]**.

Example

One can also consider the following situation:

$P = P_T$ for some $T > 0$, where $(P_t)_{t \geq 0}$ is continuous time hyperbounded Markov process with invariant measure π .

- In this case π will satisfy a log-Sobolev inequality with $I - \frac{1}{2}(P + P^*)$ as infinitesimal generator.
- and we can look at numerical schemes (Euler scheme) for approximating hypercontractive diffusion processes
- Note that in many situations the hypercontractivity property is preserved.